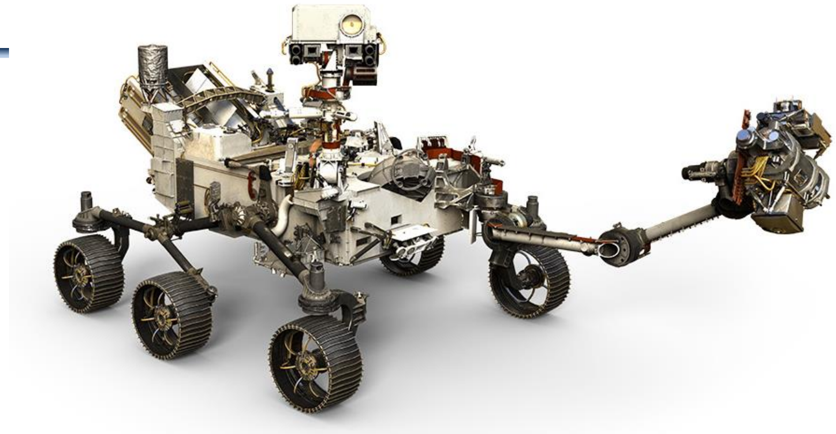
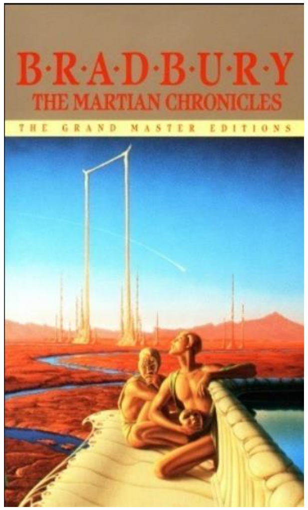


You Don’t Have to be a Rocket Scientist: JMP Martian Chronicles



October 20, 2017

Kristo Kriechbaum, Jet Propulsion Lab California Institute of Technology
Kristopher.L.Kriechbaum@jpl.nasa.gov

Jim Wisnowski, Adsurgo LLC
james.wisnowski@adsurgo.com

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Mars 2020 Rover

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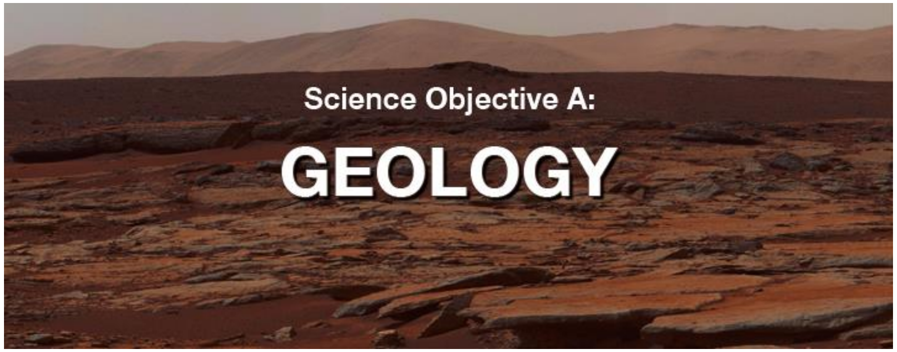
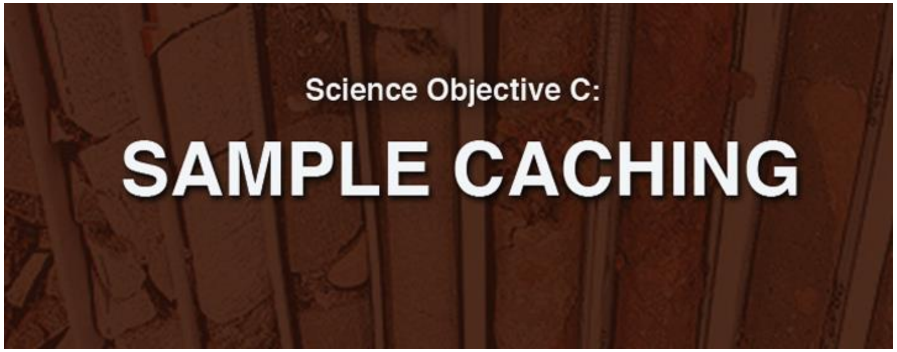
California Institute of Technology

- The Mars 2020 rover will robotically explore the red planet’s surface for at least 1 Martian year (687 Earth days)
- Builds on success of Mars Science Laboratory’s Curiosity Rover to minimize program risk





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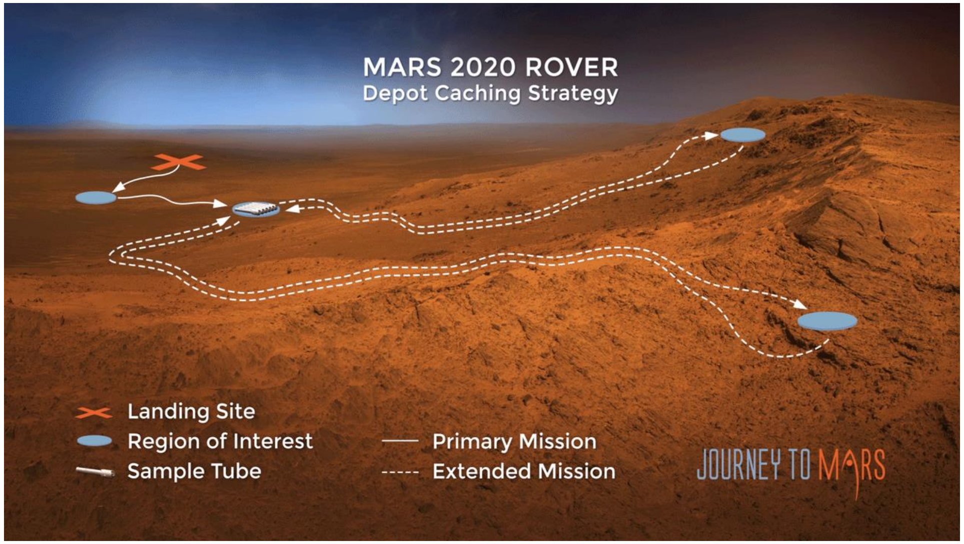
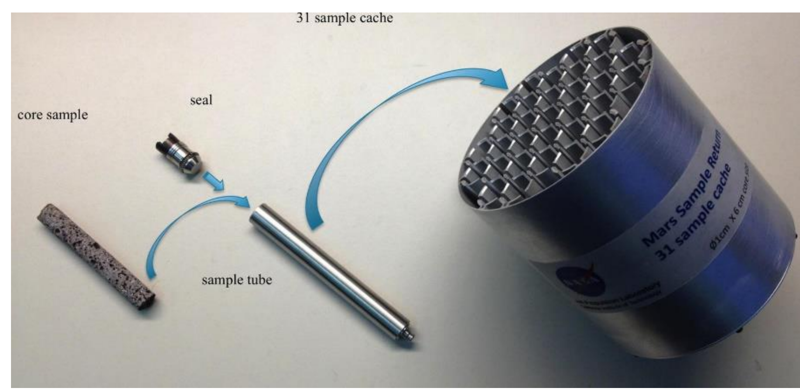
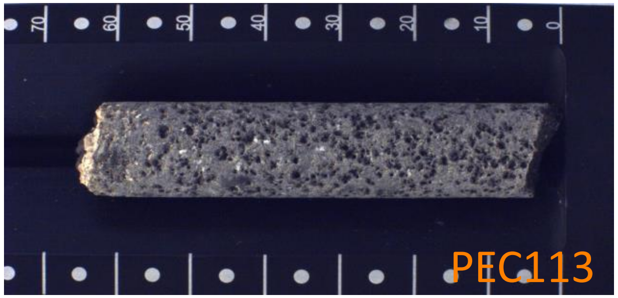
Sample Caching Subsystem





Subsystem Design

- We don't get to control Mars!
  - Subsystem design highly informed by testing
- Key requirements:
  - Collect ~40 cores of varying sample types
  - Core quality - Best core has a few number of large pieces
  - Samples must be "hermetically" sealed
- Measurable responses
  - Core quality
    - Mass and number of pieces to pass through sieves of 2, 5, 10 and >10 mm
    - Sample volume
  - Drilling Performance
    - Avg cycle sideload
    - Avg cycle percussion current
    - Avg drilling torque
    - Avg percussion power
    - Avg rate of penetration
  - Seal leak rate



Vignette 1.
Complex Distribution

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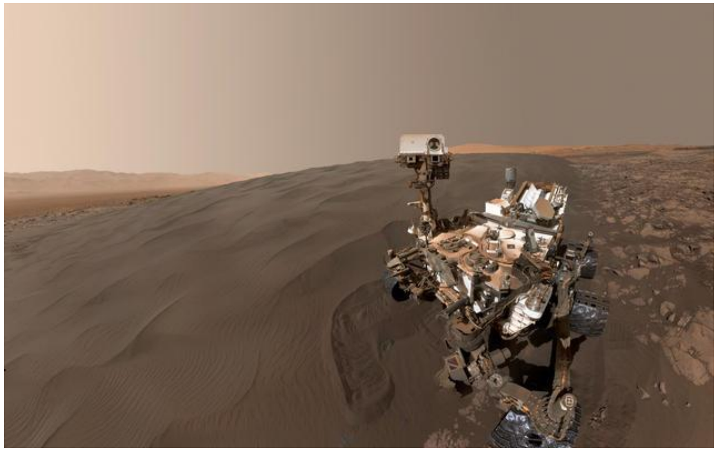
California Institute of Technology

- Problem: What is the overall distribution for Core Total Mass given we have test data for the 4 types of rocks but at much different percentages than expected for 2020 missions
- Platforms and topics: data cleaning, data visualization, filtering, fitting non-normal distributions, simulation
- Methodology: For each rock type, determine the best distribution and parameters, generate 100,000 * (expected percent on Mars) observations, concatenate all 4 random variates, fit all 100,000 observations to a new distribution
- Results:
  - Log Generalized Gamma is best fit
  - Dynamic exploration with profilers



Vignette 1. Complex Distribution

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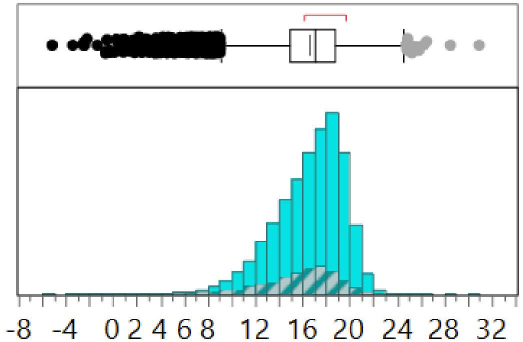
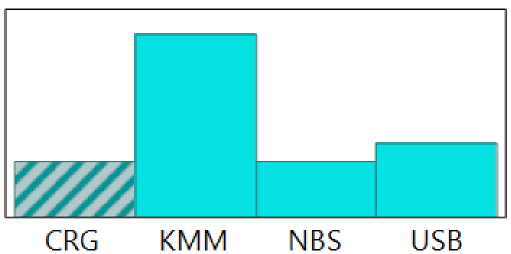


RockCode



Frequencies

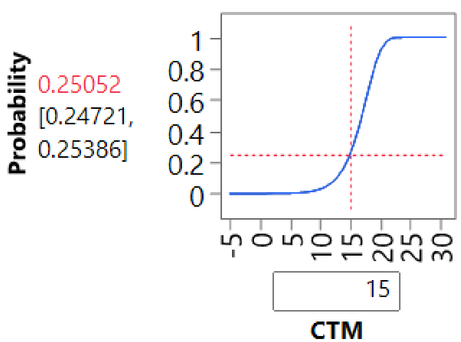
Level	Count	Prob
CRG	15000	0.15000
KMM	50000	0.50000
NBS	15000	0.15000
USB	20000	0.20000
Total	100000	1.00000

N Missing 0
4 Levels

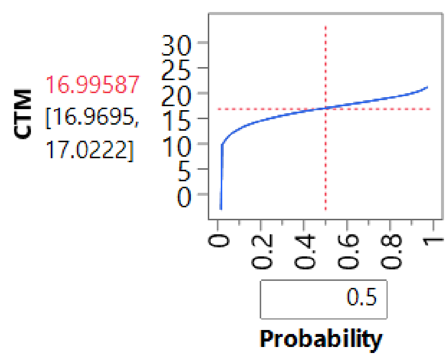
Model Comparisons

Distribution	AICc
Log Generalized Gamma	483924.04
SEV	484454.23
Logistic	494677.33
Normal	495485.46
LEV	538932.46

Distribution Profiler



Quantile Profiler



Vignette 2. Modelling Bit Wear

- Problem: How can we model the impact of bit wear on drill performance metrics?
- Platforms and topics: data visualization, fit curve, nonlinear modelling, column switcher, multivariate, fit model stepwise
- Methodology: Measure bit wear 4 times, fit candidate nonlinear models, create new control variable as bit wear, run regression models
- Results:
  - Bit wear approximated well by Logistic 3Parameter Sigmoid Curve
  - Makes sense from physics of failure/degradation models
  - Highly correlated with Time in USB rocks
  - Useful control variable for many of the responses

Vignette 2. Modelling Bit Wear

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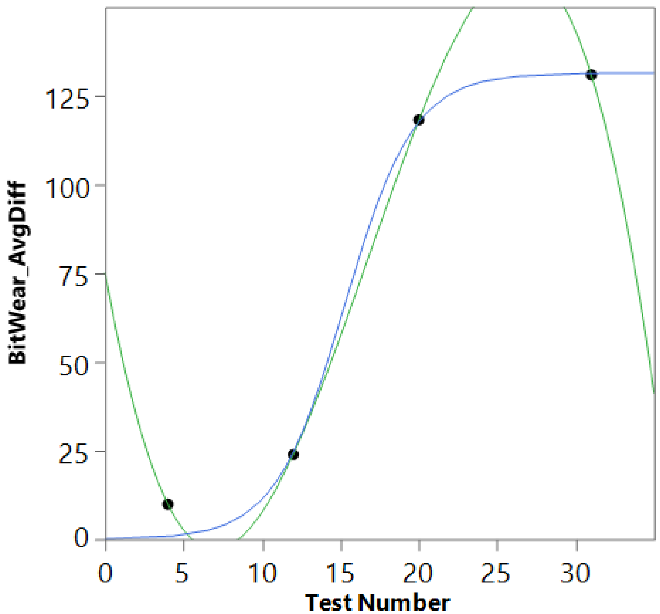


Prediction Model

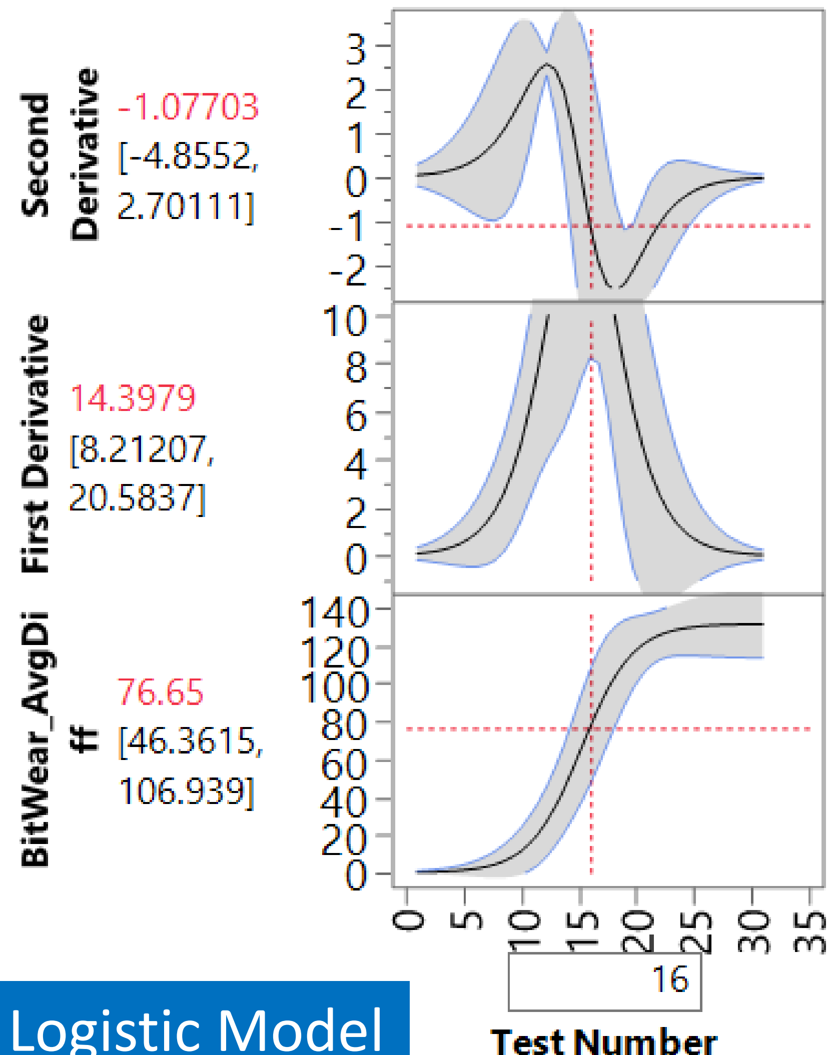
$$\frac{c}{\left(1+\mathrm{Exp}\left(-a\cdot\left(\text{Test Number}-b\right)\right)\right)}$$

a = Growth Rate

b = Inflection Point

c = Asymptote

Prediction Profiler



3 Parameter Logistic Model

Vignette 2. Modelling Bit Wear

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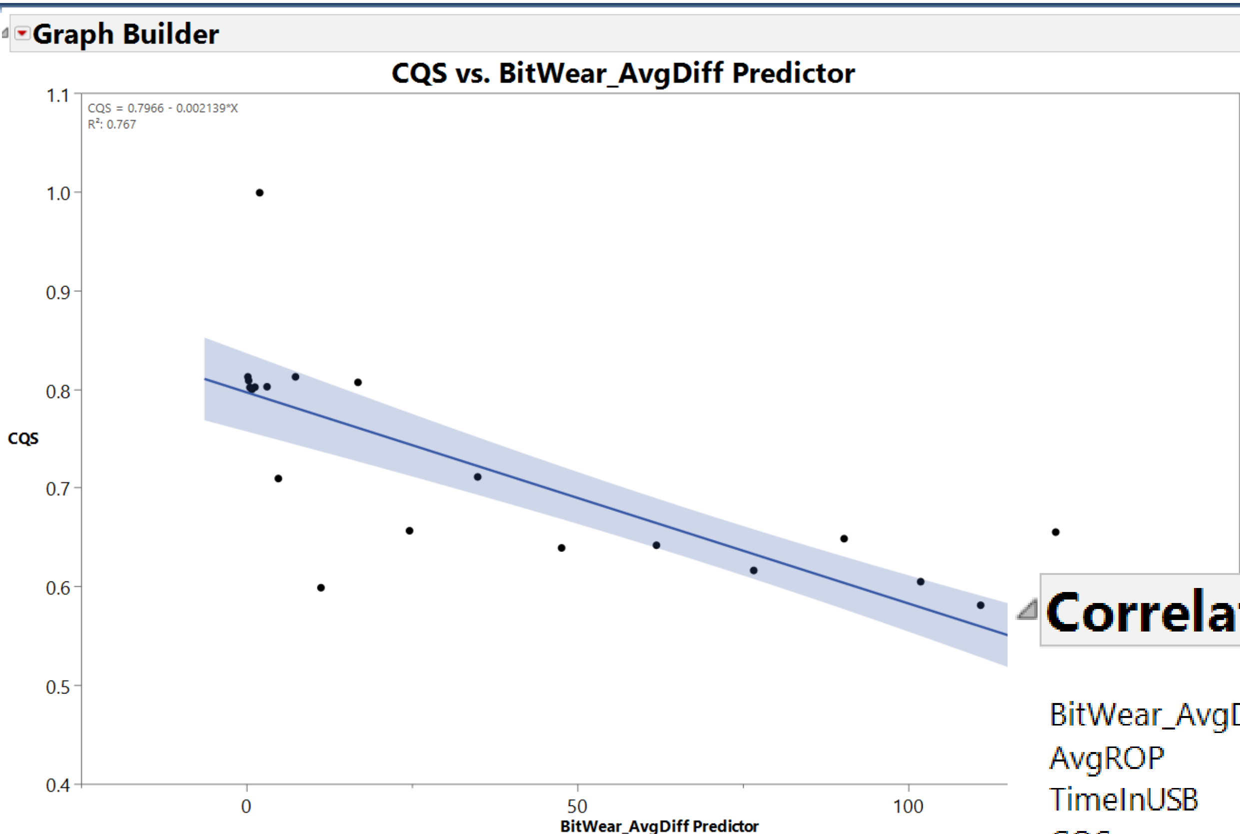

Correlations

	BitWear_AvgDiff Predictor
BitWear_AvgDiff Predictor	1.0000
AvgROP	-0.5094
TimeInUSB	0.9684
CQS	-0.8756
CoreTotalMass	-0.2533
CoreVolRatio	0.7149
TPEL_error	0.6313
CoreMassGT10mm	-0.3997
CoreNumPieces10_above	0.8828
CoreMassPerPiece_above_10mm	-0.8112
CoreVol_GT_10mm	-0.3997
CoreNumPieces	0.6037

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Vignette 2. Modelling Bit Wear

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California Institute of Technology

Stepwise Fit for CoreTotalMass

Stepwise Regression Control

Stopping Rule: Minimum BIC

Direction: Forward

Rules: Combine

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

1 rows not used due to excluded rows or missing values.

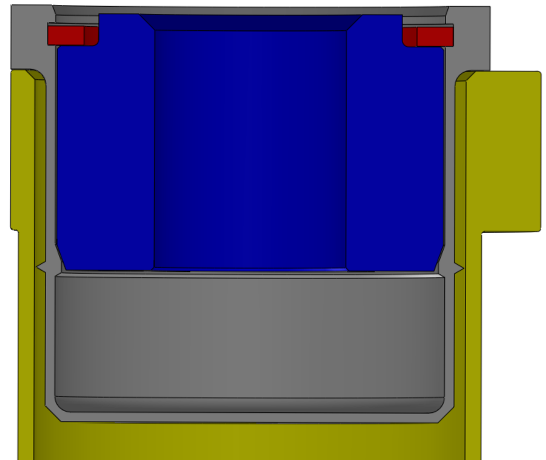
SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
14.395064	24	0.7744639	0.6662	0.5967	12.812759	6	82.19786	86.91533

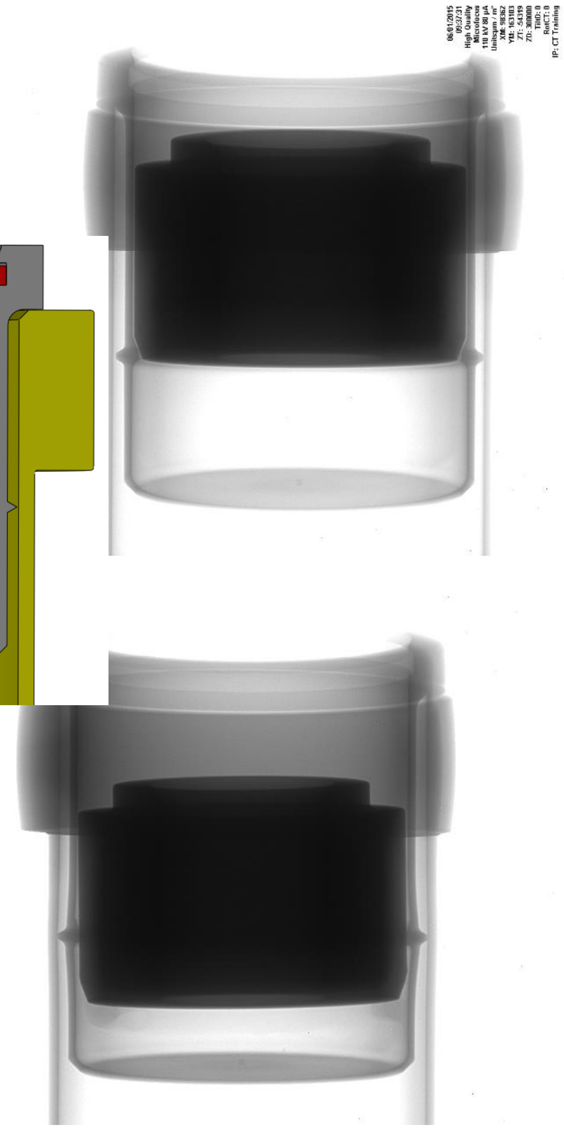
Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
✓	✓	Intercept	153.987214	1	0	0.000	1
☐	✓	BitWear_AvgDiff Predictor	-0.3984135	3	11.22554	6.239	0.00276
☐	✓	FixtureName{EDT-PEC}	79.1205223	2	13.97101	11.647	0.00029
☐	☐	DrilSpindleRate	0	1	0.034134	0.055	0.8172
☐	☐	AvgCycleWOB	0	1	1.22575	2.141	0.15696
☐	☐	Bits_ToothRakeAngle	0	0	0	.	.
☐	✓	DrillingOrientation	-4842.4669	2	10.07633	8.400	0.00172
☐	☐	AbsPercLevel	0	1	0.738844	1.244	0.27615
☐	✓	(BitWear_AvgDiff Predictor-66.8819)*FixtureName{EDT-PEC}	-1.2538818	1	6.88123	11.473	0.00243
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(DrilSpindleRate-197.933)	0	2	0.096273	0.074	0.92884
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(AvgCycleWOB-79.9826)	0	2	1.9251	1.698	0.20614
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(Bits_ToothRakeAngle--20)	0	0	0	.	.
☐	✓	(BitWear_AvgDiff Predictor-66.8819)*(DrillingOrientation-0.01718)	75.7241276	1	9.366442	15.616	0.0006
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(AbsPercLevel-32.8331)	0	2	1.526238	1.305	0.29146
☐	☐	FixtureName{EDT-PEC}*(DrilSpindleRate-197.933)	0	0	0	.	.

Vignette 3. Space Filling Designs

- Problem: Hermetic seal performance is highly dependent on line load, but it is not directly measurable! Line load is estimated via nonlinear FEA model
- Platforms and topics: space filling predictive modeling, profiler and optimization
- Methodology: Create space filling with candidate factors, fit neural holding back a few runs as validat
- Results:
  - Simple neural network model captures the nonlinearities
  - First form of line load model used before sealing test to compute ideal part dimensions
  - Second form of line load model used after sealing test to estimate actual achieved line load





Vignette 3.
Space Filling Design

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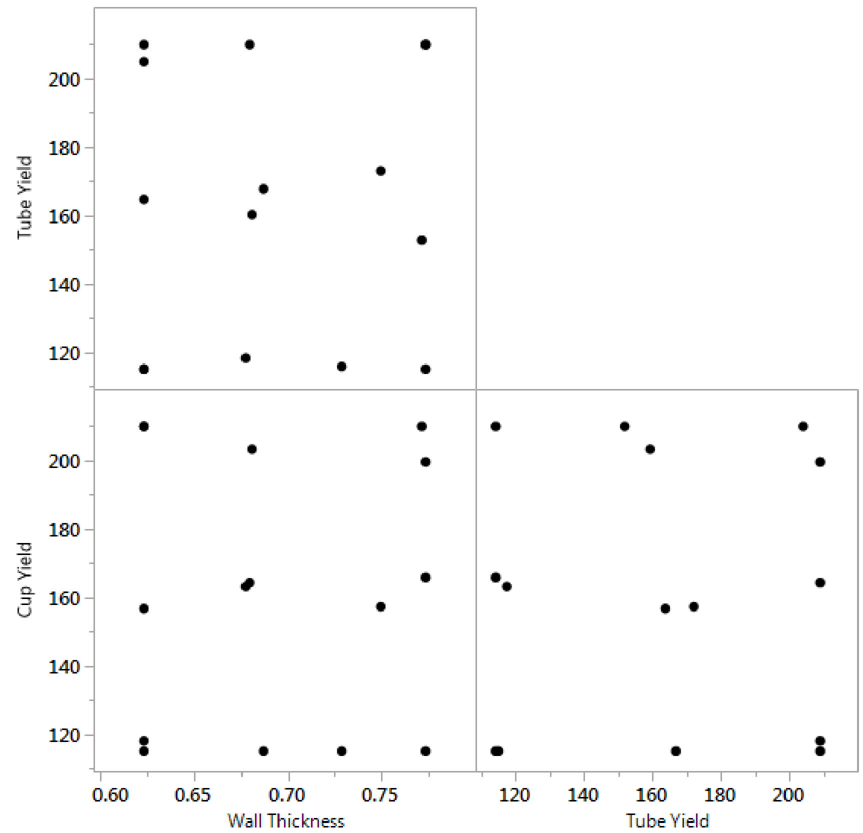
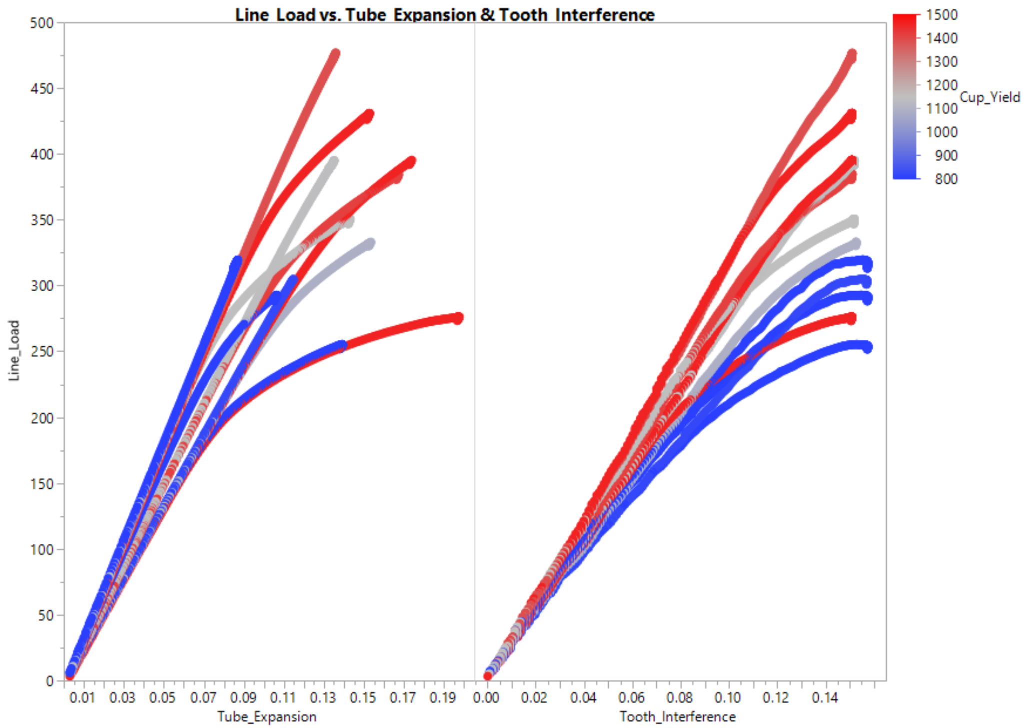
- Space filling design with 3 factors
- 15 runs chosen as a good balance between filling the space and not overwhelming the FEA analyst



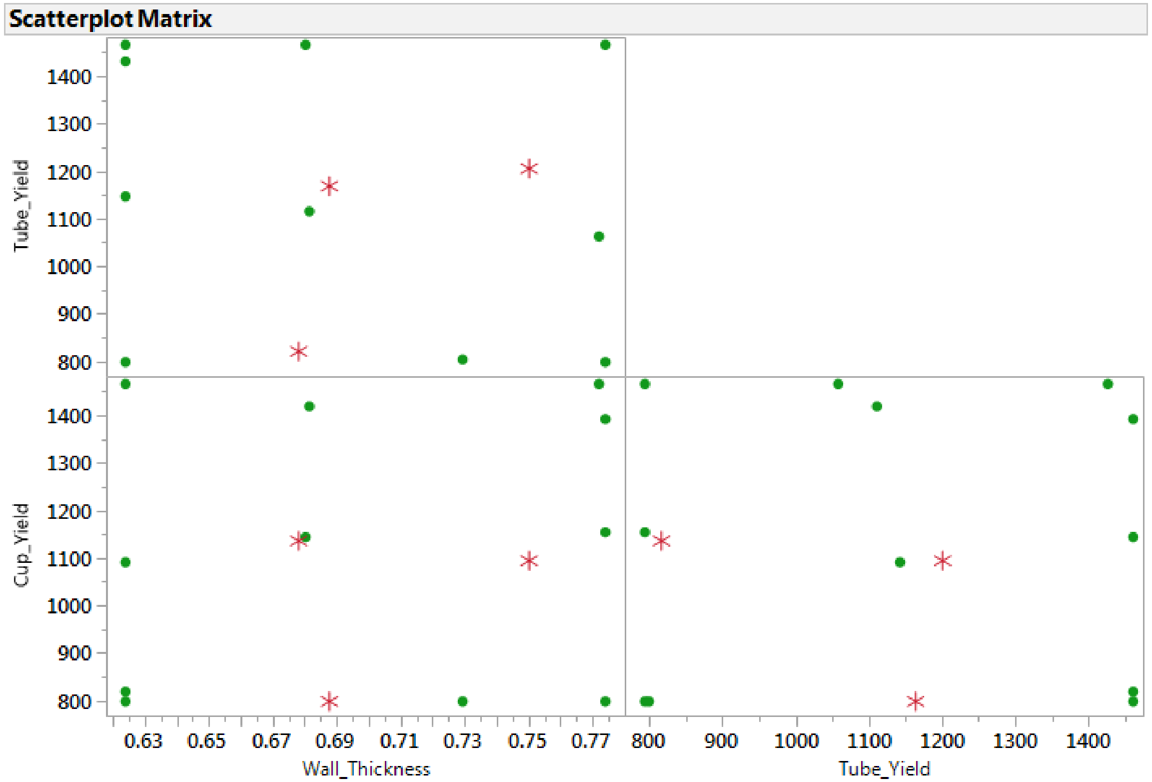
Vignette 3. Space Filling Design

- Single FEA run gives 100's of datapoints for Tooth Interference and Tube Expansion



Vignette 3.
Space Filling Design

- 3 runs randomly selected to hold back for validation



Vignette 3.
Space Filling Design

- Something with profiler?

Training

Line_Load

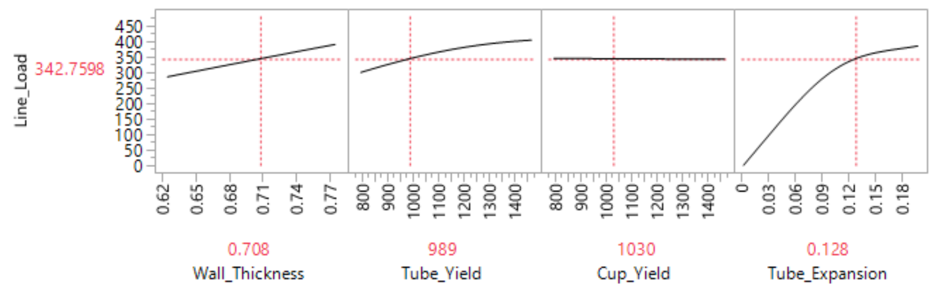
Measures	Value
RSquare	0.9998587
RMSE	1.4252988
Mean Abs Dev	1.1331251
-LogLikelihood	7800.8348
SSE	8936.4661
Sum Freq	4399

Validation

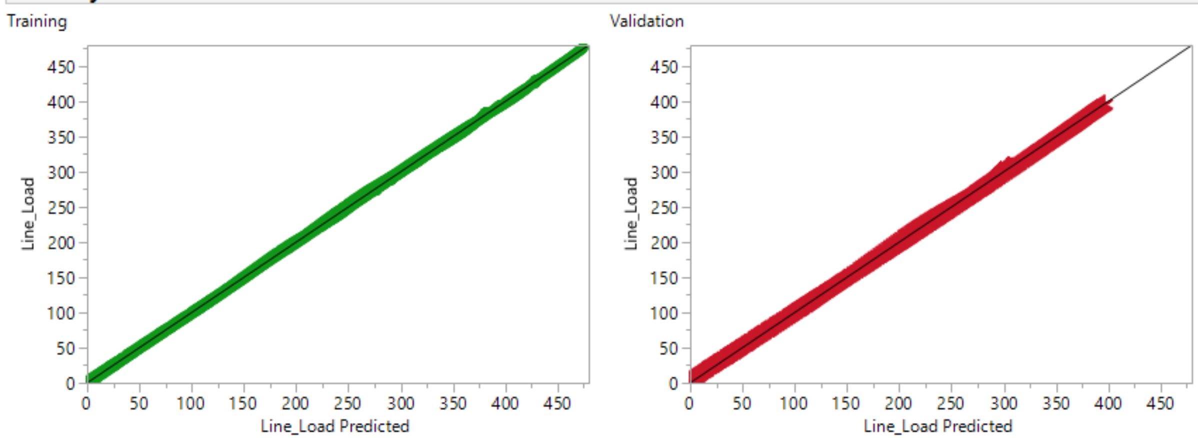
Line_Load

Measures	Value
RSquare	0.9997298
RMSE	1.8032011
Mean Abs Dev	1.4909835
-LogLikelihood	2161.1482
SSE	3498.651
Sum Freq	1076

Prediction Profiler



Actual by Predicted Plot



Summary

- High priority Mars 2020 program is experimenting to accurately characterize and optimize coring performance
- Though modest in terms of number of runs with custom and definitive screening designs, many responses, factors, and covariates present many of the analytic challenges we see in “Big Data”
- Methodical approach combines data visualization and statistical modeling techniques to quickly prepare and clean data followed by interactive exploration to form valid models
- Analysis will inform design for next series of tests

Questions